The Society for engineering in agricultural, food, and biological systems

An ASAE Section Meeting Presentation

Paper Number: PNW05-1017

Spatial Variability of Apparent Electrical Conductivity and Cone Index as Measured with Sensing Technologies: Assessment and Comparison

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Written for presentation at the
2005 Pacific Northwest Section Meeting
Sponsored by ASAE
Lethbridge, Alberta, Canada
September 22-24, 2005

Abstract. Assessment and interpretation of spatial variability of soil chemical and physical properties are very important for precision farming. The spatial variability of apparent electrical conductivity

(EC_a) and penetration resistance expressed as cone index (CI) for soil compaction was investigated with Veris 3100 and Veris 3000 sensing technologies. The study was conducted at the research farm located near Williston, ND on a sandy loam soil (Sandy, mixed, frigid Entic Haplustoll).

Measurements of soil EC_a were taken using Veris 3100 guided by a parallel swathing light bar monitored with the Trimble Ag132 DGPS unit providing spatial coordinates for each measurement at shallow (0-30 cm) and deep (0-90 cm) depths. A Veris 3000 equipped with the GPS unit was also used to collect measurements of EC_a and CI that were recorded in 2 cm intervals to a depth of 90 cm on a grid sampling system. The experimental plot area mapped with this technology was approximately 1.4 ha.

The EC_a data from both Veris 3100 and Veris 3000 exhibited similar spatial trends across the field that may characterize the variability of soil for a variety of important physical and chemical properties. The coefficient of variations of EC_a from Veris 3100 and Veris 3000 were 19.2 and 11.3%, respectively. However, the averages of EC_a measurements for Veris 3100 and Veris 3000 were 4.92 and 3.31 mS/m, respectively. The EC_a mean difference, M_d between these two devices was also significantly different from zero (M_d= 1.71 mS/m; t=34.23, n=138; pr<0.01). Geostatistical tools were used to evaluate spatial dependency and assess the overall soil variability. It was found that soil ECa and CI parameters were spatially distributed and presented weak to medium spatial dependency within the mapped field area.

Further, EC_a measurements from both sensors exhibited approximately log normal distribution and the CI values were normally distributed using probability distribution functions.

The spatial data produced from this new direct sensing technology can be used as baseline for precision farming and making future management decisions.

Keywords. Precision farming, Veris, Cone index, Electrical conductivity, Geostatistics, Variability.

Introduction

Assessment and interpretation of spatial variability of soil physical and chemical characteristics are very important for precision farming and managing agricultural practices. Because of this, farmers need new, quick, reliable and inexpensive sensing technology to measure soil properties such as apparent electrical conductivity (ECa) and soil compaction that characterize soil variability in their fields. To meet this need, on-the-go sensors (electrical and electromagnetic sensors) have been developed and are available commercially that can take measurements continuously and provide detailed soil maps while traveling across a field (Mueller et al., 2003; Sudduth et al., 2003; Farahani and Buchleiter, 2004; Sudduth and Kitchen, 2004; Sudduth et al., 2004; Adamchuk, 2005; Akbar et al., 2005; and Farahani et al., 2005). The aforementioned authors concluded that the on-the-go sensors were efficient and effective tools for soil mapping and assessing soil variability for precision farming. They also concluded that spatial data collected by this advanced technology can also be used as a baseline for precision farming and future planning management practices as well as identify possible problem areas in the field.

With recent advancements in computer and sensing technology, spatial measurements of ECa and compaction have become quick, easy, and reliable for mapping and monitoring variations in these soil properties in both space and time. Therefore, surveying agricultural fields for soil electrical conductivity (ECa) and cone index (CI) using Veris 3100 and Veris 3000 sensors (Veris Technologies, 2002) is considered one of the most accurate and powerful methods of characterizing soil variability for a variety of important soil properties such as bulk density, particle size distribution, water content, salinity, and organic matter.

Traditionally, the spatial variability of soil properties has been evaluated through classical statistics and through geostatistical techniques that verify relationships among several soil samples of a specific area or field, using the study of regionalized variables (Davis, 1986).

Geostatistical analysis methods have proven to be useful for characterization and mapping spatial variation of soil properties and have also received increasing interest by soil scientists and agricultural engineers in recent years (Webster and Oliver, 2001; Corwin et al., 2003; Mueller et al., 2003; Corwin and Lesch, 2005). Geostatistics often consists of variography and kriging. Variography uses semivariograms to characterize and model the spatial variance of the data while kriging uses the modeled variance to estimate values between samples (Journal and Huijbregts, 1978).

In this paper, we used Veris 3100 and Veris 3000 on-the-go soil sensors. A Veris 3100 sensor consists of six coulter electrodes, two of which introduce an electrical potential into the soil. The remaining four coulter electrodes are spaced to measure ECa over two approximate depths, 0-30 cm (shallow) and 0-90 cm (deep). While, a Veris 3000 is a probe combined both a penetrometer and an EC sensor to measure CI and soil ECa (Veris Technologies, 2002). This Veris technology offers soil ECa and CI mapping systems that can produce detailed and geo-referenced soils maps for identifying and interpreting soil variability.

The objectives of this study were to evaluate ECa and CI for identifying and quantifying soil variability, and to compare the two Veris sensors for their ability to estimate soil properties in the field.

Geostatistics, descriptive statistics, regression analysis, and frequency distributions were conducted to examine soil ECa and CI variability at a field site in North Dakota.

Materials and Methods

Site Description and Data Acquisition

This study was conducted on a 1.4-ha, nearly level (2% slope) grassland field at the USDA-ARS Nesson Valley Research farm located approximately 23 miles east of Williston, ND (48.1640 N, 103.0986 W). The soil is classified as Lihan sandy loam soil (Sandy, mixed, frigid Entic Haplustoll). The Lihan soil series consists of very deep, somewhat excessively or well drained soils that formed in sandy alluvium, glacio-fluvial, and eolian deposits that are in places over till or sedimentary bedrock (Soil Survey Staff, 2004).

Sampling point locations (Fig. 1) were georeferenced using the Pro XRS Global Positioning System (DGPS) with differential correction from Omni STAR Inc and data of soil ECa and CI using Veris 3100 and Veris 3000, respectively, were collected in the early spring of 2005 prior to spring tillage. On April 12,Veris 3100 sensor was used to map the ECa at two depths (0-30 cm and 0-90 cm) using a parallel swathing monitored with the GPS unit providing spatial coordinates for each ECa measurement (Fig. 1). A total of 410 sampling points were created and spaced at approximately 2.8 m and only shallow measurements (0-30 cm) were used in this study.

On April 14, Veris 3000 equipped with the GPS unit was used to collect measurements of both ECa and CI that were recorded in 2-cm intervals to a depth of 90 cm. A total of 138 points were created approximately 7.6 m apart with a few points that were spaced at larger distances (10-14 m).

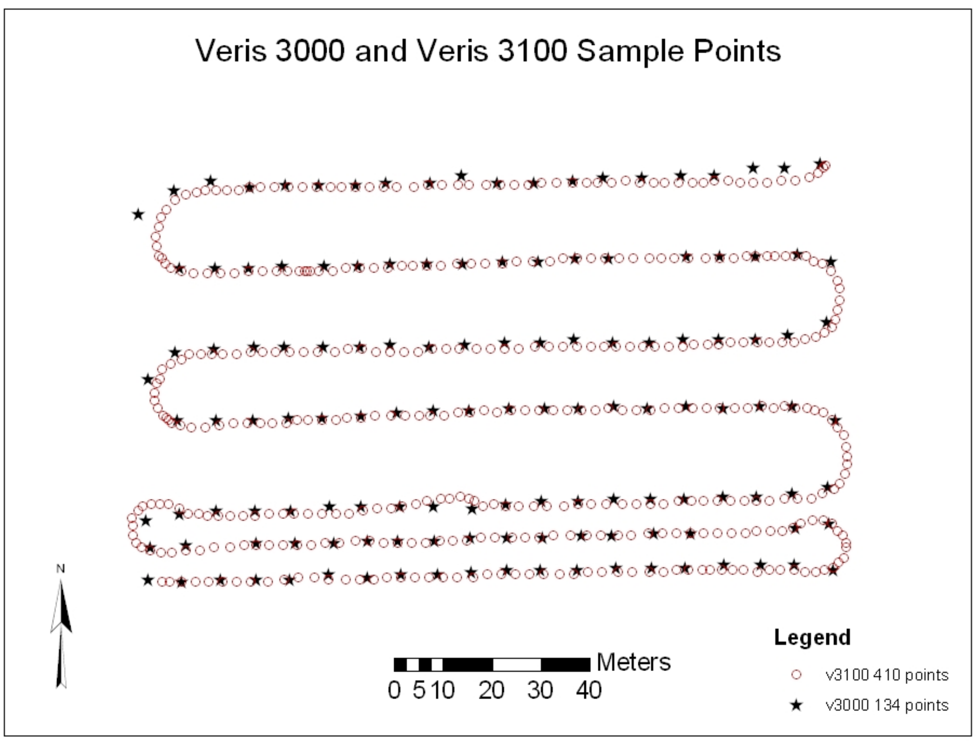

Fig. 1. Sampling points generated by both Veris 3100 and Veris 3000 for the experimental plot.

Description of Veris 3000 Profiler Model

The Veris 3000 profiler sensing unit was manufactured by Veris Technologies in Salina, Ks. The profiler consists of a mobilized probe that measure both apparent electrical conductivity (ECa) and soil compaction (CI). The probe is designed to be pulled through the field by a vehicle (Veris Technologies, 2002). The power and hydraulic unit are used to insert the penetrometer into the ground to a maximum depth of approximately 90 cm. The maximum penetration force is approximately 5 MPa with the ECa-sensing tip to prevent overload force to other mechanical components of the unit. The soil penetration force is measured by a pressure transducer and soil ECa is measured by a sensor located directly above the penetrometer tip (Veris Technologies, 2002)

The unit interfaces with the GPS and records readings and measurements of spatial coordinates, cone index, penetration speed, penetration depth, and ECa for each sensing cycle. Soil ECa is measured in milliSiemens per meter (mS/m), while penetration resistance (CI) as an indicator of soil compaction is measured in mega Pascal (MPa) (Veris Technologies, 2002).

Description of Veris 3100 Model

The Veris 3100 mapping sensor technology consists of six spaced rotating coulter electrodes mounted on a metal beam that can be pulled by any vehicle (Veris Technologies, 2002). The coulter electrodes 2 and 5 introduce an electrical potential in the soil. The remaining four coulters (1, 3, 4 and 6) are spaced to measure voltage drop and ECa over two approximate depths, 0-30 cm (shallow) and 0-90 cm (deep) based on the theory of Ohm's equation.

The unit interfaces with a differential GPS that provide geo-referenced readings of soil ECa. The soil ECa measured by this unit is in milliSiemens per meter (mS/m) (Veris Technologies, 2002).

Further information regarding Veris 3000 and Veris 3100 sensors, their description, functions, features and operational mechanism is given by Drummond et al. (2000), Veris Technologies, (2002), and Mueller et al. (2003).

Classical Statistics

The descriptive statistics (mean, variance, coefficient of variation, correlation) and probability frequency distributions of ECa and CI soil parameters were carried out with SAS software (SAS Institute, 2003) and the measured data were checked for normality of distribution using SAS probit procedure. The coefficient of variation, CV, has also been used for expressing variability on a relative basis (Eq. [1]) allowing the variability of different parameters to be compared.

$$CV\% = \frac{\sigma}{\mu} \times 100 \qquad [1]$$

Where σ and μ are standard deviation and arithmetic mean of the population, respectively.

Further, the significance of the difference, M_d, between the ECa measurements from both sensors Eq. [2]) was evaluated with a paired and unpaired-comparison t-test (SAS Institute, 2003).

$$M_d = \frac{\sum_{i=1}^{n} (Veris3100_i - \mathrm{Veris3000_i})}{n} \qquad [2]$$

The M_d in Eq. [2] measures the average difference between ECa measurements by Veris 3100 and Veris 3000. An M_d value equal to zero denotes no difference between the ECa measurements sensed by both Veris machines. A student t-test was used to determine whether M_d was significantly different from zero (SAS Institute, 2003).

Spatial Statistics

Geostatistical analysis (semivariance and kriged maps) was performed with Arc-Info (ESRI, 2005). Measurements of ECa and CI were point-ordinary kriged to produce interpolated spatial maps using a 1 m^2 grid pixel. Isotropy semivariograms were computed for each of soil parameters from both sensors using Arc-Info methods (ESRI, 2005). Spherical models were best fitted to the experimental or actual semivariance data that were interpolated using the kriging method. Semivariance is expressed in Equation [3] as described by Journal and Huijbregts (1978).

$$\gamma^*(\mathrm{h}) = \frac{1}{2N(h)} \sum_{i=1}^{N} \left(z_{\mathrm{i}} - z_{\mathrm{i+h}}\right)^2 \qquad [3]$$

Where γ^*(h) is semivariance for the interval distance class, h is the lag distance, z_i is the measured sample value at point i, z_{i+1} is the measured value at point i+h, and N(h) is the total number of pairs for lag interval h.

The semivariogram represents the mean square of the increment between two points separated by the distance h.

The spherical model that was best fitted to the experimental semivariance values for ECa and CI was defined in Eq. [4] as:

$$\gamma(h) = C_0 + C\left(\frac{3h}{2a} - \frac{1}{2}\left(\frac{h}{a}\right)^3\right) \qquad \text{for } h \le a \qquad [4]$$

and

$$\gamma(h) = C_0 + C \qquad \text{for } h > a \qquad [5]$$

where C_0 is nugget effect value, C is the spatial variance, $\underline{a}$ is the range, and h is the distance.

The sum $C_0 + C$ is the total variance (sill) for the semivariogram. The distance at which the sill value is reached, denoted as its spatial range, gives us information about the zone of the dependency influence. The range divides the sample into two groups. Observations that are located within the range are correlated or spatially dependent. This information can be used to estimate values at other points within that range. Observations beyond the range are independent observations. The slope of the semivariogram is an expression of the rate at which observations become increasingly independent with increasing distance until they approach or fluctuate around the sill. The range is often larger for a larger study area. The shape of the semivariograms reflects the nature of the overall distribution of the regionalized variables.

Results and Discussion

The spatial variability of soil ECa and CI measurements from the Veris 3100 and Veris 3000 systems were evaluated through both classical statistics and geostatistical techniques for 0-30 cm soil depth.

Analysis using Classical Statistics

Descriptive statistics of soil ECa and CI parameters measured using Veris 3100 and Veris 3000 sensors is given in Table 1. The CV of the EC_a measurements from Veris 3100 and Veris 3000 were 11.3 and 19.2%, respectively, and the CV for the CI parameter (Veris 3000 only) was 18.24%. The use of classical statistics characterized by mean, variance, coefficient of variation and range for the ECa and CI soil properties allowed grouping of field variability into low to medium (Warrick and Nielson, 1980).

Table 1 shows that CV for the ECa and CI were slightly higher than 10%, suggesting low to medium variability for the soil at this site. The Veris 3000 (n=134) sensor exhibited higher variation in ECa measurements compared to those of the Veris 3100 (n=410) due to their different sample sizes. Further, the range values of both ECa and CI measurements resulting from Veris 3100 and Veris 3000 (Table 1) were small, reflecting low soil variability within the study area.

Table 1. Statistical Summary

Statistical Measures	ECa-Veris 3100 (mS/m)	ECa Veris 3000 (mS/m)	CI (MPa)
Mean	4.92	3.22	2.135
Variance	0.31	0.38	0.152
Coefficient of variation, CV (%)	11.3	19.20	18.24
Range	2.4	2.95	2.4
Minimum	3.70	1.96	1.04
Maximum	6.10	4.91	3.44
Number of observations	410	134	134

The mean difference, M_d [Eq. 2], was also used to measure the average variation in ECa results between two sensors. The M_d in ECa measurements between Veris 3100 and Veris 3000 devices was significantly different from zero (M_d= 1.71 mS/m; t=34.23, n=134; pr<0.0001). Further, Probit functions and probability frequency distributions (not shown) exhibited approximately log-normal distributions for the ECa property from both sensors while the CI resembles a normal distribution.

Spatial Statistics

Spatial statistical methods (semivariograms and kriging) were used for characterizing and mapping spatial variation of ECa and CI soil properties. Interpolative spatial maps of soil ECa and CI measurements were created by point ordinary kriging procedure. Figs 2, 3 and 4 show the distribution of ECa and CI in the field at depth of 0-30 cm.

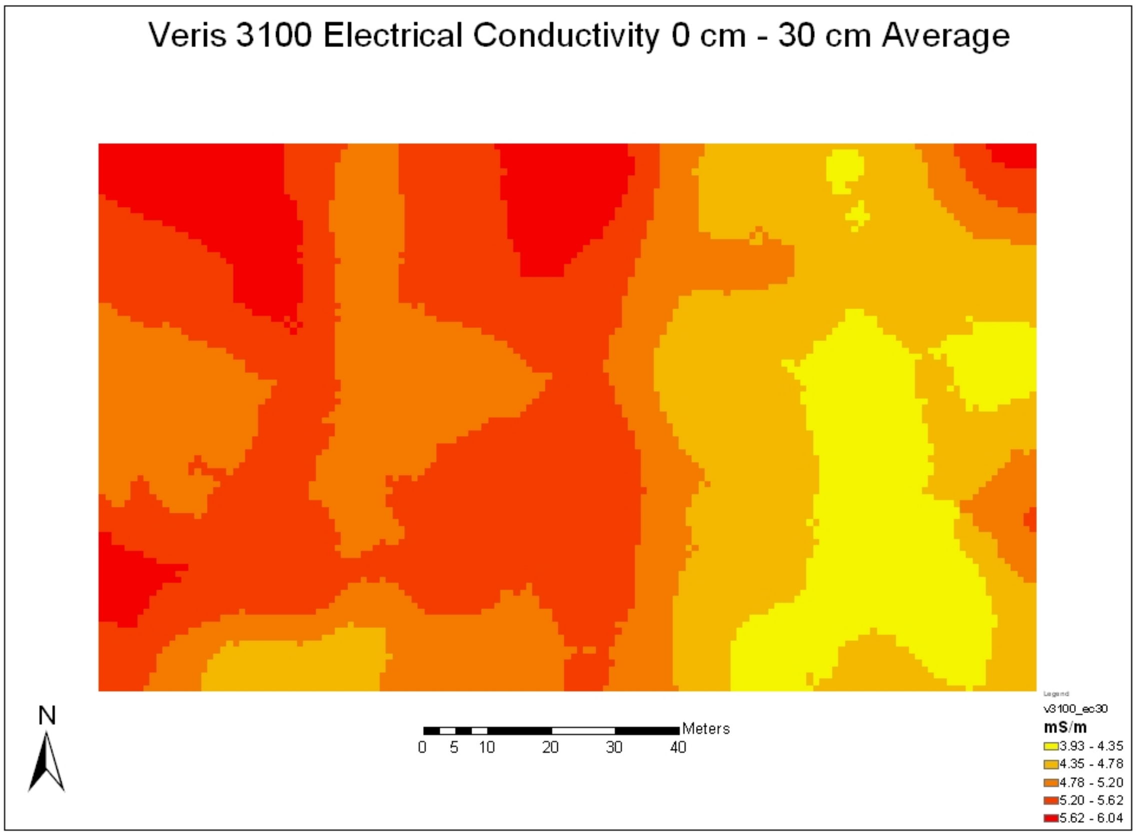

Fig 2. Ordinary kriging spatial mapping for soil ECa measured using the Veris 3100 sensor.

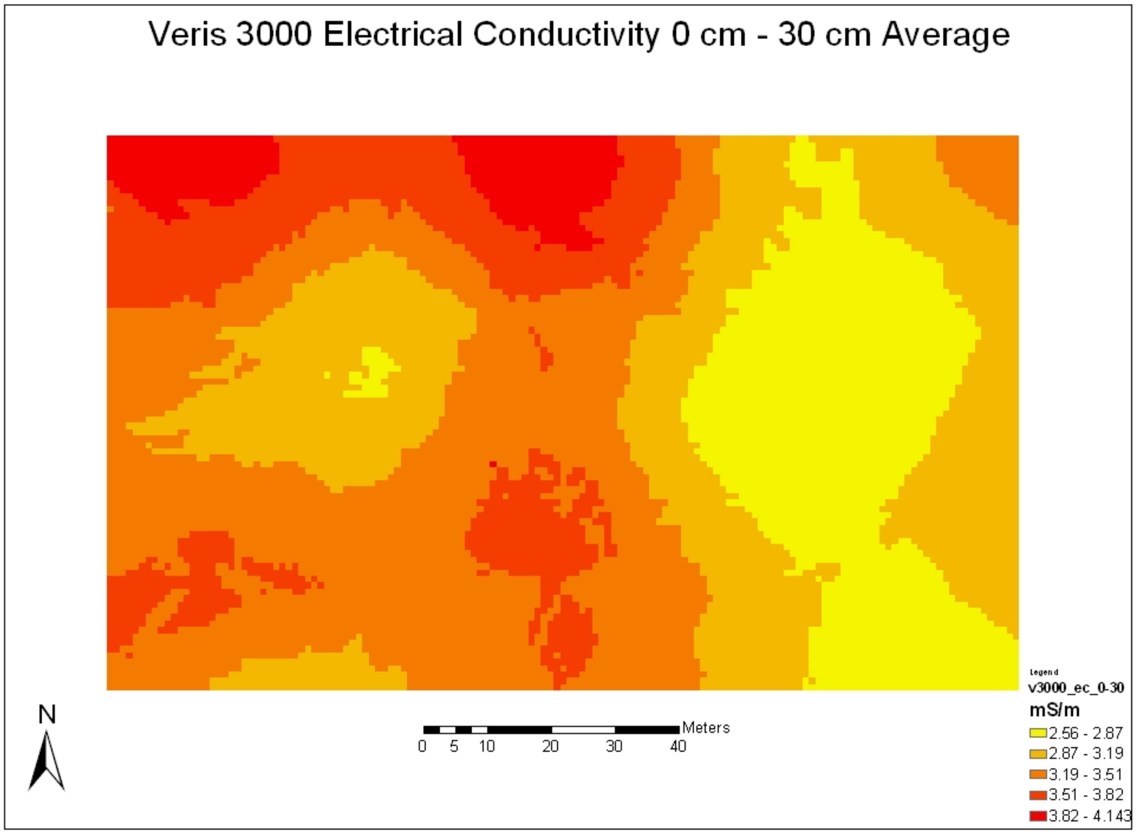

Fig 3. Ordinary kriging spatial mapping for soil ECa measured using the Veris 3000 sensor.

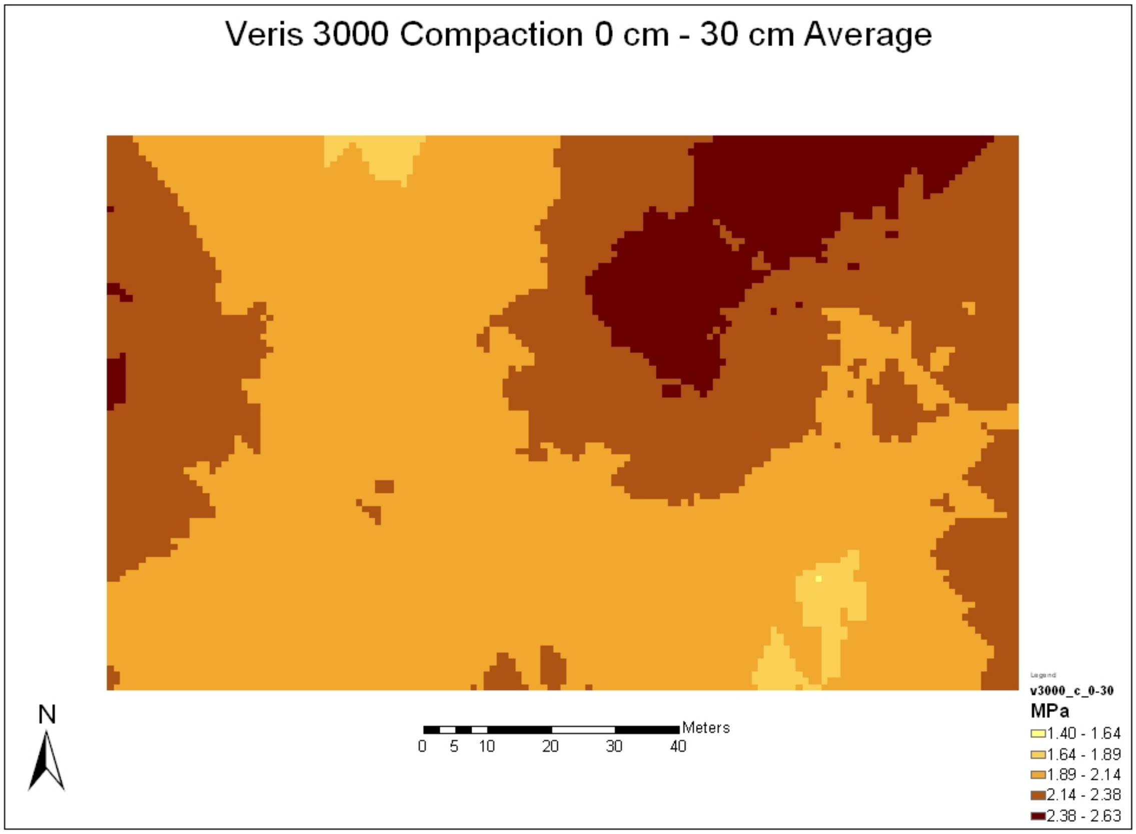

Fig 4. Ordinary Kriging spatial mapping for soil cone index (CI) using the Veris 3000 sensor.

Regarding to the spatial dependence aspect, the spherical model [Eq. 4] was most closely fit the experimental semivariograms, presenting nugget effect, sill and spatial range values to the ECa and CI soil parameters measured by Veris 3100 and Veris 3000 (Figs. 5, 6, and 7).

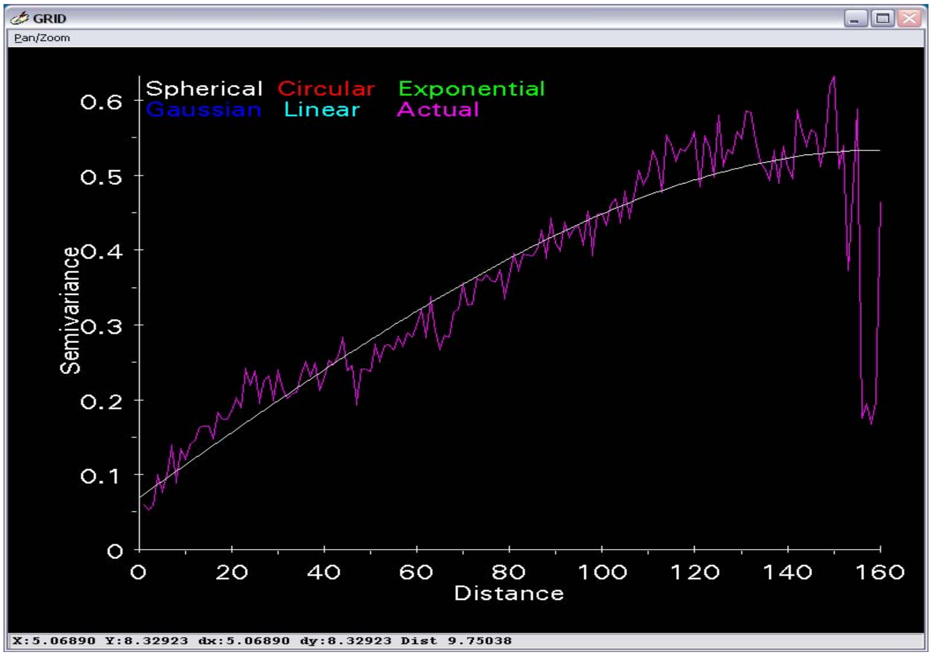

Fig. 5. Experimental and fitted semivariograms of soil ECa measured by the Veris 3100 sensor.

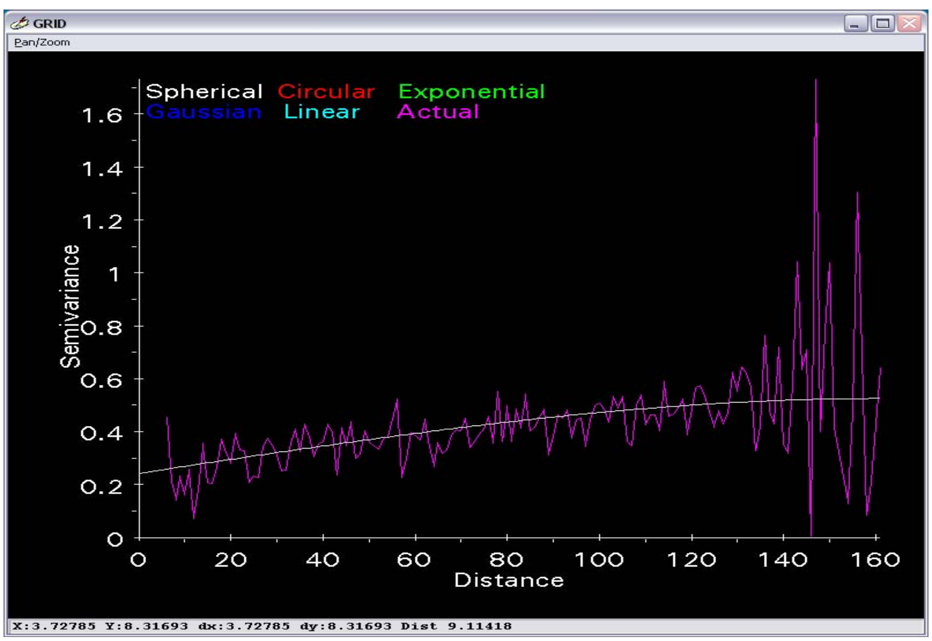

Fig. 6. Experimental and fitted semivariograms of soil ECa measured by the Veris 3000 sensor.

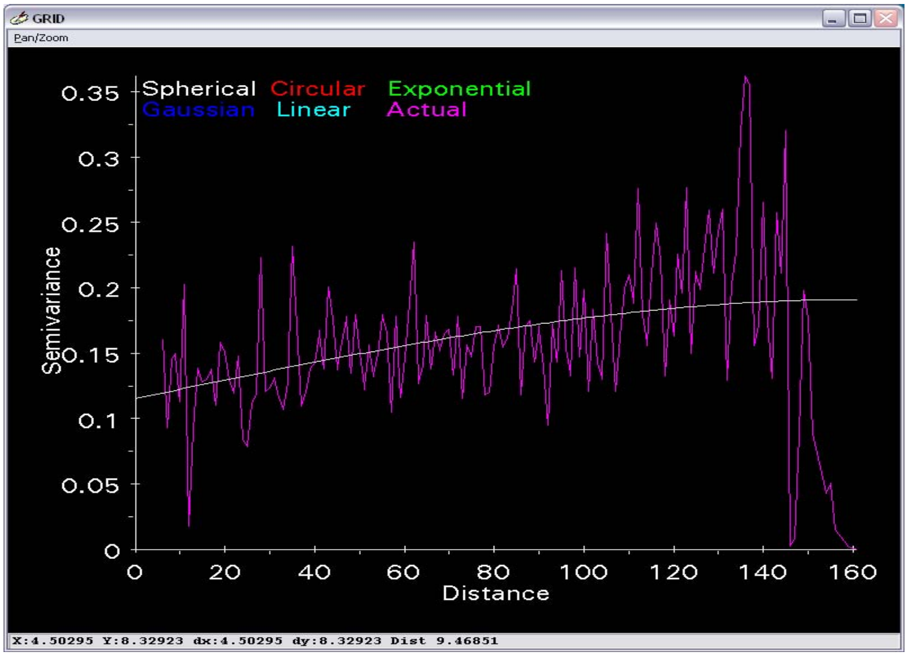

Fig. 7. Experimental and fitted semivariograms of soil CI measured by the Veris 3000 sensor.

The semivarograms were constructed to assess whether the measured data of ECa and CI variables had spatial structure or dependency. These semivarograms represent the sill values which equal the total variance of the process (Table 2). The nugget effect and the range were also observed for all soil parameters and the fitted semivariance values increased as the distance increased then flatted when they reached the sill values (Figs. 5, 6 and 7).

In order to find the distance of dependency of the spatially structured data, the range was also evaluated from the semivariogram results. Table 2 presents a summary of the geostatistical parameters nugget, variance, sill, proportion of structural variance and the range for the ECa and CI. The range of the semivariogram indicates the effective distance between samples considered to be independent from each other. The range for ECa as measured by the Veris 3100 and Veris 3000 were 161 and 160 m, respectively. It is interesting to note that the range for ECa and CI parameters were almost the same. The sill values were also close to each other for the ECa measurements from both sensors (Table 2); however, the nugget variances were considerably different for the ECa measurements. This might be attributed to different number of sampling points produced by each sensor (Table 1).

Table 2. Semivariogram spherical model kriged parameters.

Soil property	Nugget (C_0)	Spatial Variance C	Sill C_0+C	Structural Variance $P = \frac{C}{(C_0 + C)} \times 100$	Range a (m)
ECa-Veris 3100	0.070	0.464	0.533	87	160
ECa-Veris 3000	0.243	0.283	0.525	54	161
CI	0.115	0.076	0.191	40	161

The spatial range values (Figs. 3, 4 and 5) show that continuous sensor-based measurements of ECa and CI parameters were essential for proper characterization of soil variability and identifying contrasting areas in the field. The spatial structure of the data did not considerably vary between the sensors' measurements and soil parameters and the range values of spatial dependency for these soil properties were almost identical (Table 2) using spherical models with a range of 160 m.

In order to evaluate the spatial dependency of soil parameters, we used criteria similar to those of Everett and Pierce (1996) that indicated a strong spatial dependency if the proportion of the structural variance, P *(i.e.,* $P=C/(C_0+C)$), was less than 25%, to have a moderate spatial dependency if the proportion was between 25% and 75%, otherwise it has a weak spatial dependency. The structural variance proportion, P, of ECa measurements from the Veris 3100 was very high (87%) indicating a weak spatial dependency in the sampling area of the field, while the proportion of structural variance of soil parameters from the Veris 3000 were lower than that of Veris 3100 (40-54%) which characterized a moderate spatial dependency in the study area.

Using both descriptive and spatial statistics indicated that the ECa and CI Maps produced using the Veris 3100 and the Veris 3000 clearly showed uniformity representing a small scale trend of variability in the field. The ECa from both sensors exhibited higher values at the western parts of the field and presented lower values with tendency of uniformity in the remaining area. The CI showed a different scenario where the majority of higher values were located at the north western area and parts of eastern area of the field.

The findings from this study indicated the potential for using the Veris sensing technology for precision farming in order to understand and manage spatial variability of soil properties and also to identify contrasting areas within agricultural fields.

Correlation between Two Sensors' Measurements

Statistical analysis was performed to obtain correlation coefficients and develop regression relationships between the ECa measurements from Veris 3100 and ECa measurements from Veris 3000 and ECa and CI measurements from Veris 3000 (SAS Institute, 2003). A significant positive correlation ($r = 0.51$, $p<0.0001$) was found between the ECa measurements from both sensors. A simple linear regression model was proposed for predicting ECa-Veris-3000 measurements from those of ECa-Veries-3100 (Fig 8 and Eq.6).

$$ECa_{Veris\text{-}3000} = 0.562 + 0.448ECa_{Veris\text{-}3100} \quad r^2 = 0.26 \qquad [6]$$

On the other hand, a weak correlation coefficient was found between CI as an indicator of soil compaction and the ECa measurements for Veris 3000 (Fig 5).

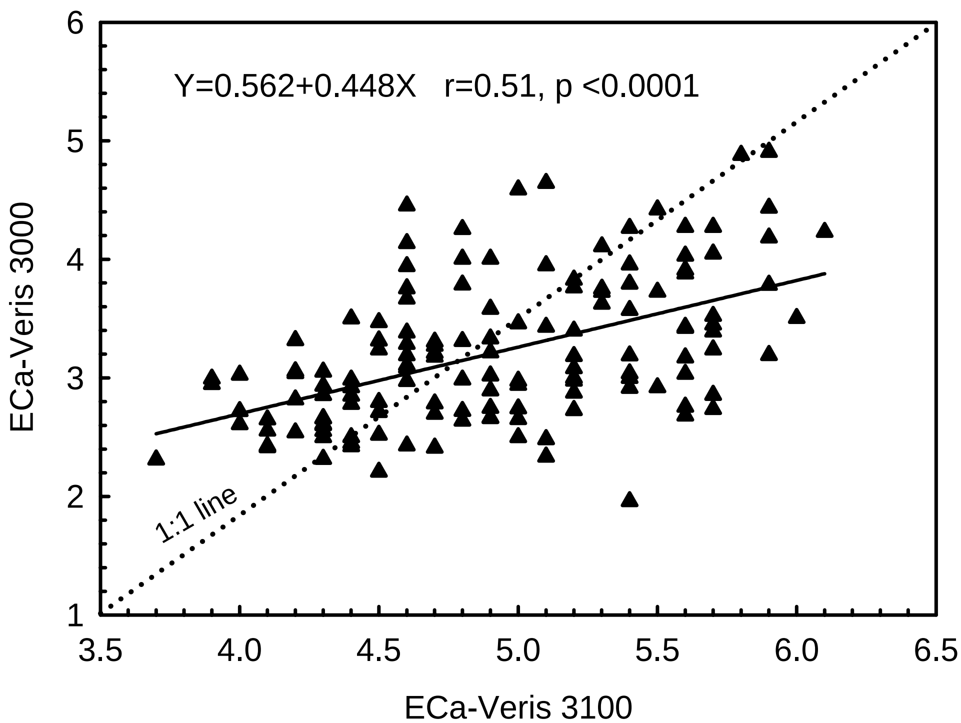

Fig. 8. Relationship between Veris 3100 and Veris 3000 for ECa on sandy loam soil at the Nesson Valley site.

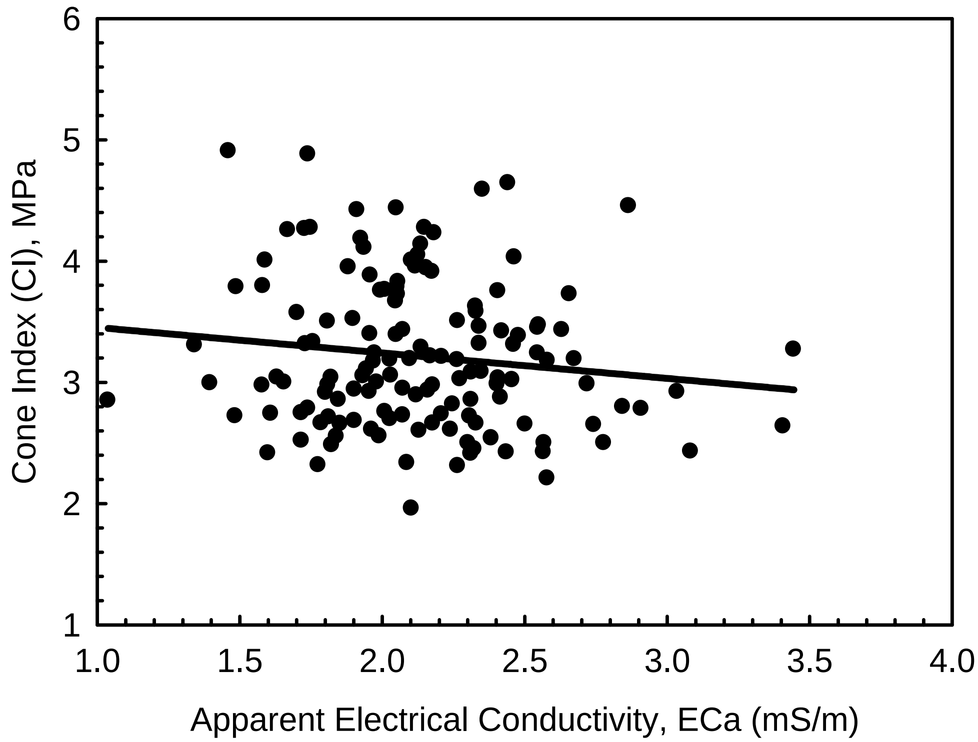

Fig. 9. Correlation between ECa and CI from Veris 3000.

Summary and Conclusions

New sensors' based measurements of soil ECa and CI can provide important information to assess and examine spatial variability for precision farming. Spatial data were collected using both Veris 3100 and Veris 3000 to investigate and evaluate spatial variability in ECa and CI for 1.4 ha grass-alfalfa field at the Nesson Valley research site in North Dakota. Descriptive statistics, semivariance analysis, and point kriging were employed to assess the magnitude and spatial range of variability in the soil measured properties. Interpolated spatial maps for ECa and CI using a 1 m^2 grid pixel may be used as a baseline for precision farming and future management decisions. The soil ECa and CI variability was spatially structured and these maps had the potential of explaining the variability within the field. We also concluded from this study, that the ECa and CI maps have the potential to aid farmers with site-specific soil use and define problematic areas within their fields.

Acknowledgements

The authors wish to express their thanks and appreciation to Mr. Dale Spracklin for preparing soil maps using Arc-Info and database software methods. The authors also thank Mr. Bryan Gebhard for his help during field mapping.

References

Adamchuck, V. 2005. Automated soil mapping on-the-go-One way of making precision agriculture more precise. Resource 12(7):12-13.

Akbar, M.A., A.L. Kenimer, S.W. Searcy, and H.A. Torbert. 2005. Soil water estimation using electromagnetic induction. Trans. ASAE 48(1):129-135.

Corwin, D.L., S.M. Lesch, P.J. Shouse, R. Soppe, and J.E. Ayers. 2003. Identifying Soil properties that influence cotton yield using soil sampling directed by apparent soil electrical conductivity. Agron. J. 95:352-364.

Corwin, D.L., and S.M. Lesch. 2005. Survey protocols for characterizing soil spatial variability with apparent soil electrical conductivity: I. survey protocols. Computers and Electronics in Agriculture 46:103-133.

Davis, J.C. 1986. Statistics and data analysis in geology. 2nd ed. John Wiley and Sons, New York. N.Y.

Drummond, P.E., C.D. Christy, and E.D. Lund. 2000. Using an automated penetrometer and soil EC probe to characterize the rooting zone. In Proc. 5th International Conference on Precision Agriculture. P.C. Robert et al., eds. pp.34-54. Madison, WI, ASA-CSSA-SSSA.

ESRI, 2005. (Online). Available URL: "http://www.esri.com" Redlands, CA

Everett, M.W., and F.J. Pierce. 1996. Variability of corn yield and soil profile nitrates in relation to site-specific N management. In Proc. 3rd International Conference on Precision Agriculture. P.C. Robert et al., eds. pp.34-54. Madison, WI, ASA-CSSA-SSSA.

Farahani, H.J., and G.W. Buchleiter. 2004. Temporal stability of soil electrical conductivity in irrigated sandy field in Colorado. Trans. ASAE 47(1):79-90.

Farahani, H.J., G.W. Buchleiter, and Brodahl. 2005. Characterization of Apparent electrical conductivity variability in irrigated sandy and non-saline fields in Colorado Trans. ASAE 48(1):155-168.

Journal, A.G. and Ch. J. Huijbregts. 1978. Mining geostatistics. Academic press Inc. New York, NY.

Mueller, T.G., N.J. Hartsock, T.S. Stombaugh, S.A. Shearer, P.L. Cornelius, and R.I. Barnhise. 2003. Soil electrical conductivity map variability in limestone soil overlain by loess. Agron. J. 95:496-507.

SAS Institute, 2003. SAS. 2004. for Windows, Version 9.1; SAS Institute, Cary, NC.

Sudduth, K.A., N.R. Kitchen, G.A. Bollero, D.G. Bullock, and W. J. Wiebold. 2003. Comparison of electromagnetic induction and direct sensing of soil electrical conductivity. Agron. J. 95:472-482.

Sudduth, K.A., S.T. Drummond, and N.R. Kitchen. 2004. Accuracy issues in electronic induction sensing of soil electrical conductivity for precision agriculture. Computer and Electronics in Agriculture 31:239-264.

Sudduth, K.A., and N.R. Kitchen. 2004. Mapping soil electrical conductivity. In: S. Stamatiads, J.M. Lynch, and J.S. Schepers (ed.) Remote sensing for agriculture and the environment, p.188-201. Peripheral Editions. Larissa, Greece.

Soil Survey Staff, 2004. Natural resources conservation service, United States Department of Agriculture. Official soil series descriptions (Online). Available URL: "http://soils.usda.gov/technical/classification/osd/index.html".

Veris Technologies. 2002. Veris Technologies (Online). Available URL: "http://www.veristech.com". Veris Technologies, Salina, KS.

Warrick, A.W., and D.R. Nielson. 1980. Spatial variability of soil physical properties in the field. In D. Hillel, Applications of Soil Physics (Eds.) pp: 319-344. Academic press, N.Y.

Webster, R., and M.A. Oliver. 2001. Geostatistics for Environmental Scientists. John Wiley & Sons. New York, NY.